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Why Does My Phone Keep Dying?: Mathematical Modeling of Smartphone Battery Usage

Summary

As smartphones become a necessity in daily life, it is crucial to find solutions to reduce battery consumption throughout the day. Although many users believe that reducing battery consumption depends only on reducing usage time, there are many other factors that go into battery consumption. This paper aims to build a ***continuous time model*** of a typical smartphone battery that returns the **state of charge(SOC)** and **time-to-empty** under different conditions.

First, we identify the primary factors of battery usage as the **smartphone display**, the **processor**, and the **smartphone network**. Each factor was identified from either the given problem statement or general knowledge of battery usage. After identifying each factor, we expanded our analysis to their respective subsystems.

For example, the smartphone display depends on the brightness scale, the screen size, and the pigment of **RGB** for each pixel. The processor depends on the usage of the processor chip and the average usage of the **processor cores**. The smartphone network depends on the idle state, WiFi and Bluetooth connections, and network (5G and LTE) usage.

Next, we use a **general additive model(GAM)** to combine all factors with their respective subsystems. This model can be adjusted for any factor, showing which components have the greatest affect on the **SOC**. The model was then converted into **python code** to generate graphical representations of the state of charge depending on the **GAM**.

Furthermore, we accounted for the active and passive use of the smartphone in our mathematical model. Actions such as streaming a show, the location services being used, and playing a phone game are active uses that will quickly deplete the **SOC**, but are typically used for short periods of time. In contrast, passive use actions are connection to Bluetooth, WiFi, or networks. These actions slowly deplete the battery, but are typically used for long periods of time.

By separating active and passive use of smartphones, the model can accurately display the **SOC** and **time-to-empty** of low, medium, and high smartphone usage.

This model was created to account for the differing outputs of the daily factors and their respective subsystems. In addition to the daily factors that affect battery usage, we also provided analysis on temperature and cycle use as long term factors for battery capacity. Future work will implement long term factors into the model to examine battery health in the life cycle.

In general, the model developed from **GAM** accounts for the primary factors and subsystems in smartphone battery usage to accurately estimate the **SOC** and **time-to-empty** of a typical smartphone battery.

Keywords: state of charge(SOC), time-to-empty, lithium ion battery(LIB), smartphone display, processor, processor cores, smartphone network, general additive model(GAM)

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1 Introduction

1.1 Background

Innovation in smartphone technology has skyrocketed in the past 20 years (Cook [2021]). It is estimated that almost 4.69 billion people use smartphones in 2025 and is projected to reach 5.83 billion by 2028 (Backlinko [2026]). As smartphone use continues to increase, optimizing battery usage is more essential than ever.

It is common knowledge that the easiest way to reduce battery usage is not using your smartphone. However, there are many other factors that can be adjusted slightly and drastically change the battery usage of the phone. Something as simple as connecting to WiFi or decreasing the brightness level can change the **time-to-empty** from one hour to three. Key factors such as **smartphone display**, **processor**, and **smartphone network** are essential to modeling battery use.

1.2 Problem Restatement

For this problem, we are asked to create a ***continuous time model*** of battery usage that shows the **SOC** and predicts the **time-to-empty** in varying conditions. We are given ideas of variables that could affect the battery usage such as; the display screen size and brightness, processor load, network activity, and background applications on the smartphone.

The first requirement is to build a ***continuous time model*** that uses a continuous-time equations or system of equations.

- Data may be used to support the model but not as a substitute
- The model may not use linear regression

The second requirement is to estimate the **SOC** and **time-to-empty** of the battery at any given time in the day.

- The model must work under different conditions (low, medium, and high usage)
- The model must show how quickly each factor depleted the battery. This is to help build recommendations for smartphone users.

The final requirement is to create a list of recommendations for smartphone users

- Recommendations must come from the results of the ***continuous time model***

2 Assumptions and Justifications

To simplify the problem, we make the following basic assumptions, each of which is properly justified.

- **Assumption 1:** WiFi, LTE, and 5G network connections are mutually exclusive.

  Justification: *Since WiFi implies that the smartphone is not connected to cellular data, and 5G is not compatible with LTE, a smartphone cannot be connected to more than one type of network.*

- **Assumption 2:** The voltage is constant in all smartphones and does not fluctuate over time.

  Justification: *Voltage fluctuations for one smartphone are minimal, and the voltage of the battery across smartphones is similar.*

- **Assumption 3:** For the screen of any smartphone, every unit of area has the same average gray scale.

  Justification: *It is not feasible to obtain the gray scale of each pixel on a screen, but multiplying the average gray scale by the area of the screen is an easier approximation.*

- **Assumption 4:** There are three levels for the clock speed: low (384MHz), medium (1026MHz), or high state (1512MHz).

  Justification: *There is limited data on the clock speed of applications, but these are reasonable bins for a variety of smartphone applications.*

- **Assumption 5:** A smartphone user will not use their phone while charging.

  Justification: *This would over-complicate our model when the goal is to predict time to empty.*

- **Assumption 6:** The display power and idle power that an app uses is evenly distributed over the time that the app is used.

  Justification: *For our modeling tests we are using iPhone battery usage from the settings menu which does not include these variables, thus averaging these is the most accurate.*

3 Analysis of Daily Factors

3.1 Overview

In order to model the state of charge of a smartphone and predict the remaining time-to-empty, we considered that the power use depends on the **display**, **CPU**, **network**, and **idle functions**. The display will be effected by the size and colors of the screen at any given time. The CPU determines how much power each application uses. The network connection changes the amount of idle power drawn and thus adds to the total power drawn for different actions. Other idle systems draw power even when the smartphone is not being actively used.

The amount of power the display on a smartphone draws is dependent on the size, gray scale, and brightness of the display. The lowest amount of power that the display can use while on is if the brightness and gray scale are at their lowest levels. A smaller screen would also result in lower power consumption, but a smaller phone may have a smaller battery thus we are considering the smartphone has already been purchased and therefore display size cannot be changed. As a result, the highest power consumption is when the brightness and gray scale are at their highest levels.

The CPU is the main driver of power usage from the chip and distributes power based on the actions taken on the smartphone. We generalize smartphone applications to have a low, medium, or high clock speed. The higher the clock speed, the more power is drawn from the CPU. The amount of power drawn from smartphone applications is also dependent on network connectivity and thus effects the overall power consumed by the chip as well.

The power consumed by a smartphone due to network connectivity is dependent on the WiFi status and Bluetooth status, as well as the actions taken while the smartphone is on different networks. For an idle smartphone, power consumption tends to be lowest when it is connected to WiFi and Bluetooth is shut off, and highest when it is connected to 5G internet and Bluetooth is roaming, i.e. searching for Bluetooth devices. There are many other combinations, we assume a smartphone is either connected to the Global System for Mobile Communications (GSM) which is currently on the fifth generation (5G), Long-Term Evolution (LTE) network, or WiFi and that Bluetooth is either connected to a number of devices, searching for connections, or off. This gives a smartphone nine possible states under our model and the power consumed by different actions, e.g. phone calls, streaming, or emails, is different under each state.

3.2 Display Power Consumption

Modern smartphones use an AMOLED screen to display content to the users. This screen serves as a substantial power draw on the phone as long as it is turned on. The power of a display is equal to the sum of each pixel on the display.

$$P_{disp} = \sum_i P_{pixel_i}$$

Where $pixel_i$ is the ith pixel on the screen.

From (Chen et al. [2013]) we can derive the equation for the power draw of a single pixel:

$$P_{pixel} = (R_c^{2.2} + G_c^{2.2} + B_c^{2.2})Ba$$

Where R_c, G_c, and B_c are the gray level of red, green, and blue light, respectively, B is the brightness factor (from 0 to 1), and a is the power factor parameter.

As we want to sum the pixels, we can simplify the equation by taking the average gray scale of the whole screen ($\bar{I}$). If we assume that every unit of area has the same average gray scale we can multiply by area to get the total display power.

$$P_{disp} = \bar{I}^{2.2} AB\alpha$$

With the parameter α in units of milliwatts per millimeter squared.

Using the figures and data in (Chen et al. [2013]), we can fit alpha to our expected maximum display power for different gray scales and brightnesses. Our final model for display power is thus. . .

$$P_{disp} = (552 \cdot 10^{-9})\bar{I}^{2.2} AB \tag{1}$$

. . . where A is area in mm, B is the brightness factor normalized from 0 to 1, and $\bar{I}$ is the average gray scale of the screen from 0 to 255.

3.3 Network and Processor Power Consumption

3.3.1 Processor Chip

Our research indicates that the chip power draw is dominated by the CPU, with RAM and other factors contributing negligible power draw in comparison.

$$P_{chip} \approx P_{CPU}$$

Due to the inability to measure data on CPU idle states and application compute time, we take a very simplified approach to modeling CPU power draw. We begin with the simplified CPU power model:

$$P_{CPU} \approx \alpha_{freq} U_{CPU} + \beta_{freq}$$

Using the data and figures in (Zhang et al. [2015]), we estimated the frequency parameters for three frequencies: 384MHz, 1026MHz, and 1512MHz. As further frequency based CPU usage data is limited, we simplify future calculations by classifying applications into one of these three frequencies. We thus assume that the clock speed is running at either a low (384MHz), medium (1026MHz), or high state (1512MHz).

Due to the significant approximations to the P_{chip} model, we cannot accurately attribute U_{CPU} to CPU usage. We thus generalize this to be U_{chip} to represent the general strain on the chip. As this ideally is mostly comprised of CPU usage, we expect U_{chip} to vary between 0 and 1 (ideally below 0.5). We will fit the usage parameter U_{chip} to known data from our personal smartphones.

Streaming information is another high power consumer. Since the action of streaming information to your phone is often initiated by an application, we will include it in our P_{chip} model. Our research suggests that the power draw from streaming information is mostly dependent on your network connectivity: whether you are streaming over 5G, LTE, or wifi. We thus derive a constant piecewise model S_{net}] from (Gupta et al. [2024]),

$$S_{net} = \begin{cases} 566 & \text{WiFi} \\ 749 & \text{LTE} \\ 859 & \text{5G} \\ 0 & \text{not streaming} \end{cases}$$

We thus have our final chip power model:

$$P_{chip} = \alpha_{freq} U_{chip} + \beta_{freq} + S_{net} \tag{2}$$

3.3.2 Idle Power Consumption

We generalize P_{idle} to account for all of the components that draw power when the phone is not in use (no applications are running including background ones). We deduce that when no applications are running and the display is off, the main factors that vary P_{idle} are network, WiFi, and Bluetooth connectivity.

Whenever your phone is connected to anything wireless, the phone must always exert power to be ready to receive a signal from its wireless connection. This passive power consumption is largely dependent on what network you are connected to and if you are connected to any Bluetooth devices: P_{net} and P_{BT} (respectively). Additionally, the phone exerts power to search for new devices to connect to. Since phones spend a relatively show amount of time searching for Bluetooth devices (typically only a few seconds), we will focus on the power consumed by searching for WiFi networks (P_{search}). Finally, phones are constantly consuming a small amount of power to remain operational, even if not network is connected or being searched for (P_0).

$$P_{idle} = P_{net} + P_{BT} + P_{search} + P_0 \tag{3}$$

From (Gupta et al. [2024]), (Ding et al. [2013]), and (Friedman et al. [2013]), we estimate these values to be the following,

$$P_{net} = \begin{cases} 260 & \text{5G} \\ 160 & \text{LTE} \\ 32 & \text{WiFi} \\ 0 & \text{none} \end{cases}$$

$$P_{BT} = \begin{cases} 88 & \text{connected to at least 1 Bluetooth device} \\ 0 & \text{not connected to any Bluetooth devices} \end{cases}$$

$$P_{search} = \begin{cases} 72 & \text{searching for WiFi network} \\ 0 & \text{not searching for WiFi network} \end{cases}$$

$$P_0 = 20$$

4 Analysis of Long Term Factors

4.1 Battery Temperature

Increased temperature both externally and internally can permanently affect the battery capacity of a smartphone. Many smartphones have safety mechanisms in place to stop a smartphone from reaching extreme temperatures that cause irreversible damage, such as corrosion or battery explosion. **Lithium-ion batteries(LIBs)** are responsible for up to 80% of all electronic devices on the market due to their long cycle life, high voltage-to-weight ratio and low maintenance needs **[clean energy institute]**. The capacity of LIBs can change with prolonged use and extreme temperature. This section will discuss how temperature differences can affect a LIB.

4.1.1 General Structure of a Smartphone

Presented in the following 1 is a general model of the components of a smartphone. Firstly, there is a **backplate**, and then one of the two **graphite sheets** is placed next. The next layer holds the **heat pipe, AP,** and **LIB** together. The heat pipe typically uses water as the working fluid due to its high thermal exchange properties. However, sometimes a thermal grease or thermal pad is used in the replacement of a heat pipe (Kim et al. [2019]).

The battery is located to the right of the heat pipe for easy temperature regulation. The next layer is a metal bracket that holds these layers in place by connecting to the backplate, and then the second **graphite sheet** and **the front glass** go on the smartphone.

The placement of each layer is essential to the smartphone as it helps with internal and external temperature management for the smartphone battery. Each layer has a thermal resistance to external temperature, lowering the heat transfer to the internal battery.

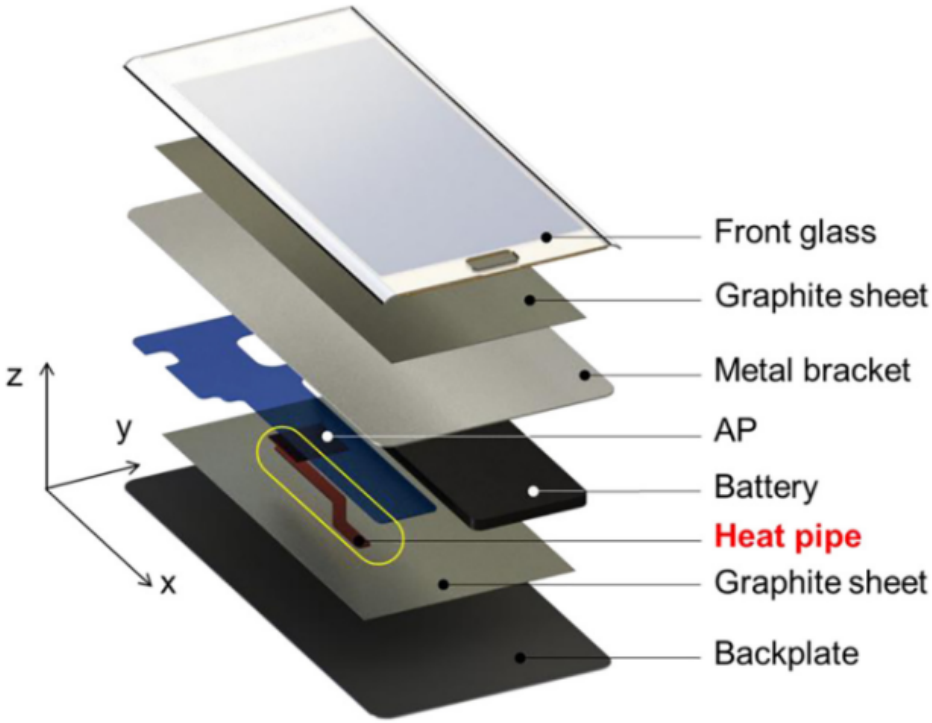


Figure 1: Model of Smartphone

4.1.2 Chemistry of LIB

Lithium ion batteries utilize a **charge/discharge cycle** between the cathode, lithium cobalt oxide, and the anode, graphite, to transfer lithium ions between the separator inside the battery (Ma et al. [2018]). Lithium has a smaller atomic weight and radius for the charge/discharge cycle compared to other standard atoms such as hydrogen and helium. This means that lithium has a high energy density, meaning that lithium can carry a high voltage while maintaining a low mass. The lithium ion charge/discharge cycle creates a quick, rechargeable battery. Below is a figure of the cathode and anode system for LIBs,

The redox reactions for discharge of a lithium-ion battery are shown below [thermal impact reference],

$$xLi^{+} + Fe^{3+}PO_4 + xe^{-} \rightarrow LiFe^{2+}PO_4 \tag{4}$$

$$Li_xC_6 \rightarrow xLi^{+} = C_6 + xe^{-} \tag{5}$$

The chemical structure of lithium and their redox reactions in the charge/discharge cycle have many advantages for compact battery storage and efficient recharging. However, large temperature changes can still drastically deplete the battery health of LIBs. Research for LIBs is primarily focused on finding new solutions to reduce the negative effects that temperature has on battery health.

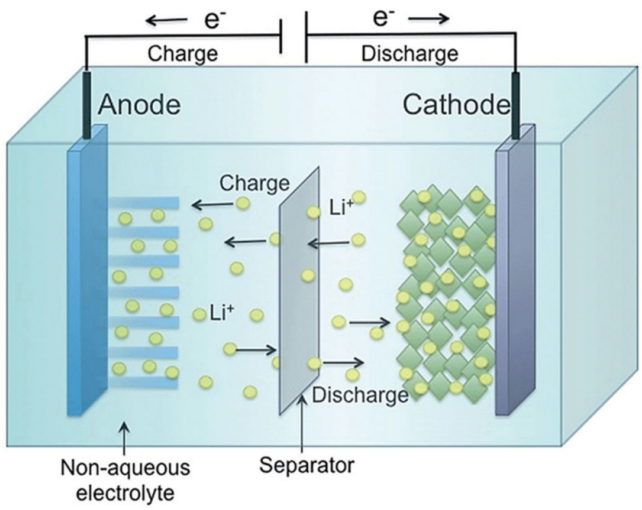


Figure 2: Diagram of Lithium Ion Battery Operations

4.1.3 Thermodynamics of LIB

Heat transfer between the exterior surface of a smartphone, **the front glass** and **backplate**, and internal heat generation with the battery, **heat pipe**, and **AP** are essential to manage the impact of temperature on battery health. The heat transfer for LIBs can be described as,

$$\dot{Q}_{battery} = \dot{Q}_{internal} + \dot{Q}_{external} \tag{6}$$

The internal heat generation of a LIB comes from voltage drops due to internal resistance and from the chemical reactions during the **charge/discharge cycle**. This can be described as (Kim et al. [2019]),

$$\dot{Q}_{internal} = \dot{Q}_{joule} + \dot{Q}_{react} = I(U_{SOC} - U_{OCV}) - IT_{int}(\frac{\partial U_{OCV,SOC}}{\partial T}) \tag{7}$$

Where, **I** is the current flowing through the LIB and $\mathbf{T_{int}}$ is the internal temperature of the battery. The subscripts **OCV** and **SOC** stand for open circuit voltage and state of charge, respectively.

The external heat transfer of a LIB depends on the external temperature,**T** the surface area exposed to the external temperature,**A**, and the heat transfer coefficient of the exposed material,**h**. This can be described as,

$$\dot{Q}_{external} = \int \int_A T_{ext}(T, x) h dA \tag{8}$$

The two above equations give a basis in the general thermodynamic progress for external heat transfer and internal heat generation for a smartphone. These equations can be used to develop the **heat conduction module**, which further describes the correlation between battery capacity and increased temperatures.

4.1.4 Heat Conduction Module

The **heat conduction module** and the corresponding boundary condition for heat generation on the smartphone is described as (Kim et al. [2019]),

$$\int \int \rho(T,x)\frac{\partial T}{\partial x}(T,\overline{x})dV = \int \int_s k(T,x) * \nabla T(x,t)ds + \int \int_V \int S(x,T)dV \tag{9}$$

$$h(T(t) - T_o(t)) + k\frac{\partial T(t)}{\partial n} = 0 \tag{10}$$

This equation defines the boundaries for heat generation and identifies heat generation as a summation of external surface temperatures and internal volumetric temperatures. This equation can be used to model the temperature from different layers of the smartphone; surface, AP, and battery, as time continues.

The temperature reports from each layer of the smartphone account for the overall affect of temperature on the battery. The external surface temperature along with the internal heat generation from the battery gives us an understanding of the temperature that the battery is under at any given time.

MARS is a code developed from the heat conduction module for temperature predictions for each layer depending on the discharge rate from lithium transfer (Kim et al. [2019]). Below are three different cases of the temperature at each layer depending on the discharge rate of (a)0.4C (b)0.6C and (c)1.0C

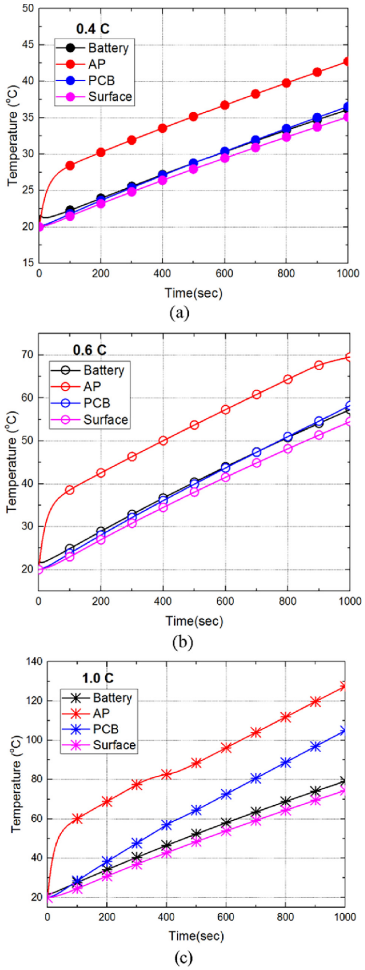


Figure 3: Graphical results from MARS

From 3, it shows that as the discharge rate increases with smartphone usage, all layers of the device get increasingly warmer. The increase in temperature results in the AP and the heat pipe exerting more energy to regulate the internal and external temperatures on the smartphone.

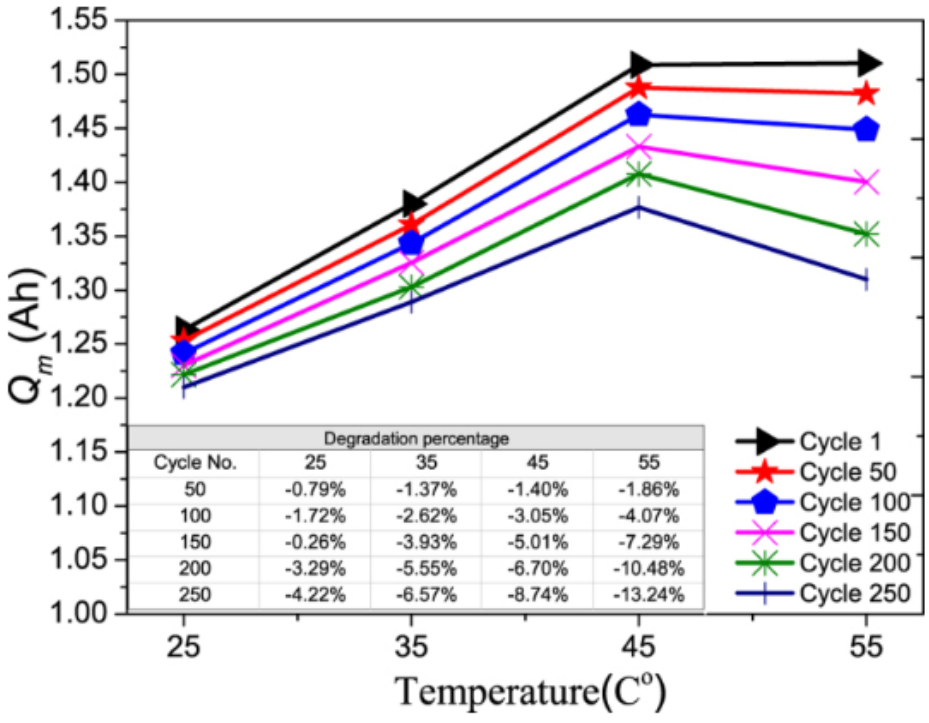
4.2 Battery Health

It is common knowledge that batteries lose capacity over prolonged use. Extreme or consistently high temperatures can have the same affect that time has on a battery's capacity. This section will discuss how increasing temperature affects the cycle life of a LIB and decreases overall battery health.

4.2.1 Life Cycle

Battery capacity depletion from temperature damage is proportional to the life cycle of battery's usage. When a LIB is exposed to high temperatures, the initial battery capacity can increase. This happens because heat increases the speed of redox reactions that occur within the battery (Prine-Robie [2023]). However, continuing to cycle the battery in extreme temperatures will result in an irreversible depletion of battery capacity.

The figure below shows the correlation between temperature, cycles, and depletion of battery capacity (Ma et al. [2018]).



Degradation percentage				
Cycle No.	25	35	45	55
50	-0.79%	-1.37%	-1.40%	-1.86%
100	-1.72%	-2.62%	-3.05%	-4.07%
150	-0.26%	-3.93%	-5.01%	-7.29%
200	-3.29%	-5.55%	-6.70%	-10.48%
250	-4.22%	-6.57%	-8.74%	-13.24%

Figure 4: Capacity Depletion in Relation to Temperature

This graph shows the battery capacity linearly increasing for the initial cycles but eventually hitting a point and decreasing battery capacity. This shows that there is a threshold before irreversible damage is caused to a LIB. This threshold can be described as,

$$\alpha_{battery} = |\frac{n_{cycle}(T) - n_{thres}(T)}{n_{thres}(T)}| = |\frac{n_{cycle}(T)}{n_{thres}(T)} - 1| \tag{11}$$

Where $\mathbf{n_{cycle}}$ is the number of cycles and $\mathbf{n_{thres}}$ is the number of cycles the smartphone has been through where the increased temperature is still producing an expansion of battery capacity. Notability, both of these variables are dependent on the temperature at which the smartphone is cycling through.

5 Model of Smartphone Battery Usage

5.1 Model Derivation

To derive our model for the state of charge (SOC) of a smartphone over time, we first quantified how charged a smartphone is by the energy in its battery. Smartphones advertise often how much charge their batteries can hold in milliampere-hours (mAh). However, energy is a more useful measurement with regards to how much 'work' your phone is doing. We thus begin with the equation for charge (Q) in terms of energy (E) and the voltage across the battery (V).

$$Q = \frac{E}{V} \tag{12}$$

We can assume voltage to be constant as its fluctuations are minimal in a healthy battery (on the order of millivolts). We thus proceed to analyze energy, keeping in mind that it is proportional to the charge of the phone battery.

The rate at which the phone battery loses energy is equal to how much power the phone is using at that time. The negative sign is convention as we will henceforth refer to P as the amount of power being *drawn* from the phone.

$$P(t) = -\frac{dE}{dt}$$

$$E(t) = -\int_0^t P(\tau)d\tau + E_0 \tag{13}$$

If we know the power draw of the phone battery over time $P(t)$ and the phone battery's initial energy at $t = 0$ (E_0), we can solve for $E(t)$.

The power draw on a phone battery is equal to the sum of all the unique components' power draws. These components must not contribute to the power draw of other components if they are to be represented as a sum. We have determined the main unique power components of a smartphone to be the following:

- **display**: the power drawn by the screen
- **chip**: the power drawn to run an application
- **idle**: the constant power draw on the phone when it is not in use.

Assuming these components make up all the power draw of a smartphone with no overlap, our equation for power becomes the following.

$$P(t) = P_{disp}(t) + P_{chip}(t) + P_{idle} \tag{14}$$

We now use our previous analysis for display, CPU, network, and idle power to finalize our power model.

5.2 Final Model

From the analysis of Daily Factors, we have our final power model:

$$P(t) = \alpha_{disp}\bar{I}^{2.2}ABf(t) + \alpha_{freq}(t)U_{chip}(t) + \beta_{freq}(t) + S_{net}(t) + P_{net}(t) + P_{BT}(t) + P_{search}(t) + P_0 \tag{15}$$

A summary of each variable can be seen in Table 1.

variable	component	description	units
α_{disp}	Display	Display power parameter	$552 \cdot 10^{-9}\ mW/mm^2$
$\bar{I}$	Display	Average gray scale of the screen	0 to 255 unit-less
A	Display	Display screen area	mm^2
B	Display	Screen brightness	0 to 1 unit-less
$f(t)$	Display	If the screen is on at time t	0 or 1 unit-less
$\alpha_{freq}(t)$	chip	Frequency slope parameter at time t	mW
$U_{chip}(t)$	chip	Usage parameter of chip at time t	unit-less
$\beta_{freq}(t)$	chip	Frequency intercept parameter at time t	mW
$S_{net}(t)$	chip	Additional power consumption from streaming at time t	mW
$P_{net}(t)$	Idle	Power consumption from network connection at time t	mW
$P_{BT}(t)$	Idle	Power consumption from BT devices connected at time t	mW
$P_{search}(t)$	Idle	Power consumption from searching for WiFi at time t	mW
P_0	Idle	Constant base power consumption	mW

5.3 Analysis

We seek to test our model by simulating real world phone usage across a day. We specifically analyzed the time from when the user unplugs their phone to the time they plug it in for the last time that day. Our model and simulation assumes that the user never uses their phone while it is charging.

The data we used for our simulations is from iPhone battery power analysis, a feature built into all modern iPhones. This feature allows you to see how much phone battery each app that you used that day consumed. This feature does not have a section for display power or idle power, so we assume that this power is distributed evenly across time of usage for each app. In this way we simulate iPhone

usage as a series of events and connection changes. Events include both active (initiated by the user) and background (not initiated by the user) app usage. We ran three simulations, each with different phones, usage patterns, and timing.

5.4 Results of Model

We tested our model using iPhone battery usage data from our personal iPhones. Apple settings reports a percentage battery usage for each app along with how long the app was used. Since the total percentage adds up to the total battery usage, we assume that idle power draw over the usage time of that app is included in its total battery usage. We use this data to fit U_{chip}, α_{freq}, and β_{freq} uniquely to each app that was used. We manually input what network the tester was connected to and if they were paired with any Bluetooth devices at the time they were using each app. Brightness was assumed to be constant throughout the day.

We demonstrated two tests without changing any parameters (reflecting the tester's actual settings). Figure 5 is a high phone usage tester, while Figure 6 is a low phone usage tester. The horizontal axis is hours since the phone was unplugged. In the high usage case the phone is predicted to die 20 hours after being unplugged (assuming they don't charge their phone throughout the day). For example, if they unplugged their phone at 6 am, their phone is predicted to die by 10 pm. The low usage test case has a much higher prediction of 38 hours after the phone is unplugged. We now analyze each component's effect on the phone's predicted time until depletion.

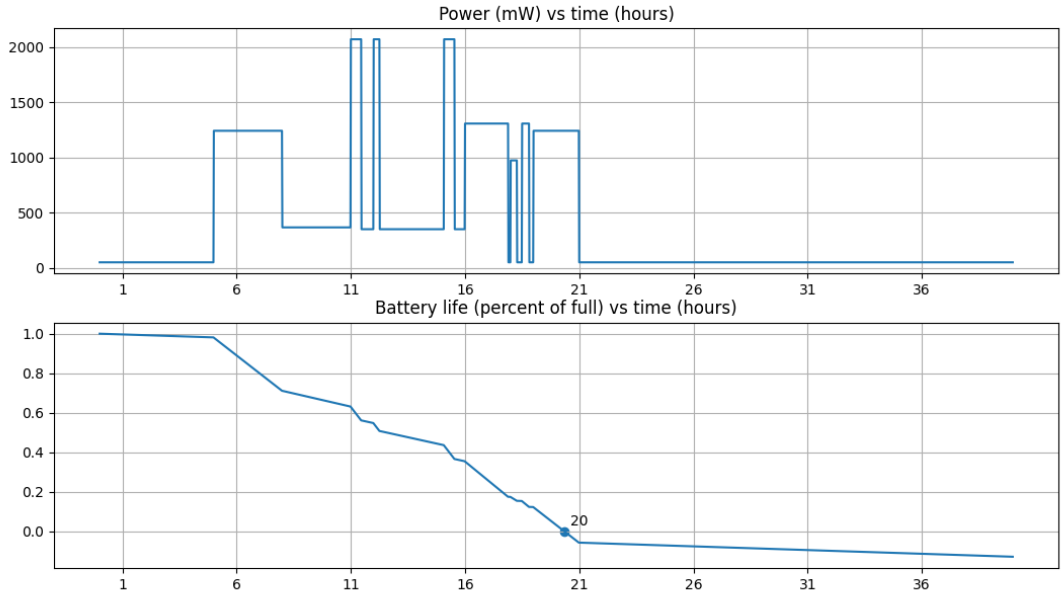


Figure 5: High usage analysis

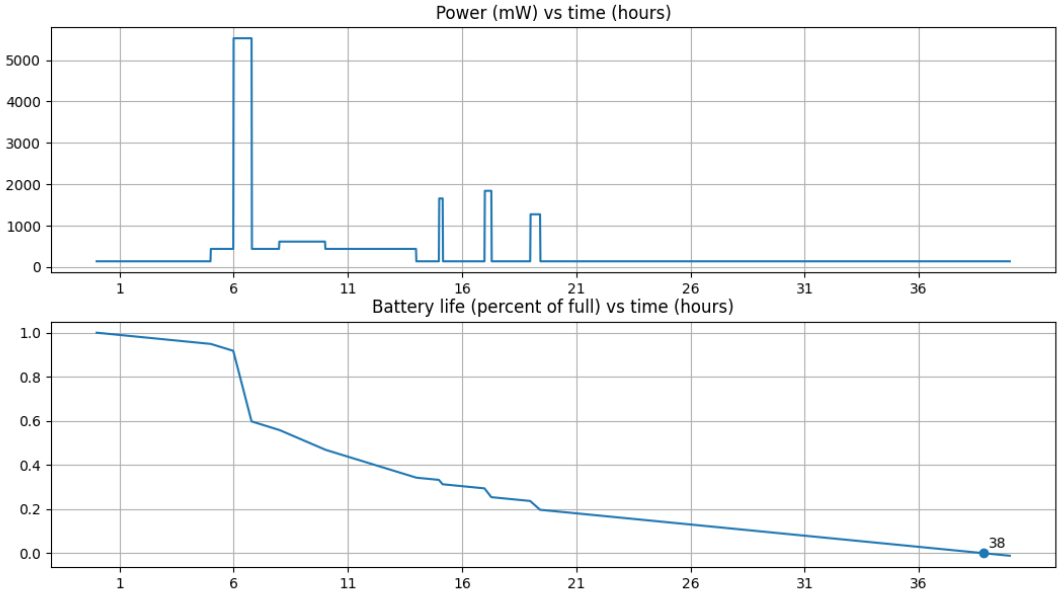


Figure 6: Low usage analysis

5.4.1 Brightness

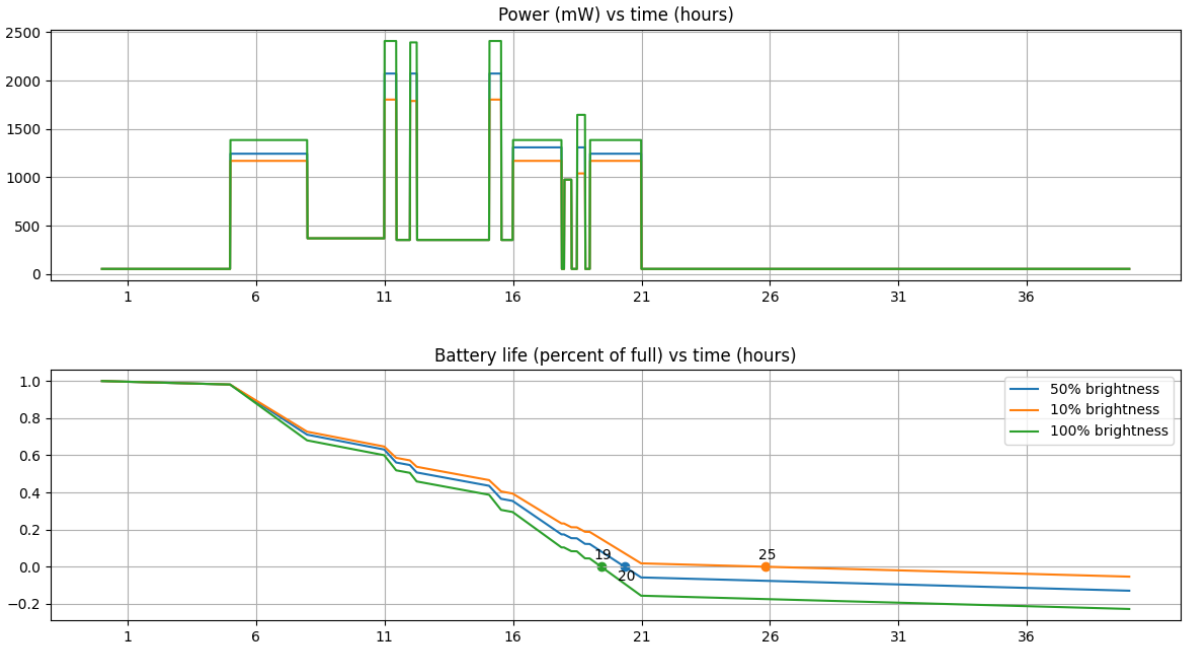


Figure 7: Brightness analysis

The high usage test case had a consistent brightness of around 50 percent. Our simulations in Figure 7 indicate that increasing brightness to 100 percent had little impact (losing about an hour). However, decreasing brightness yielded significant savings, with a decrease to 10 percent brightness increasing battery life by 5 hours. This low level of brightness is only suitable in dark environments, highlighting the effectiveness of aggressive auto screen dimming.

5.4.2 Screen Size

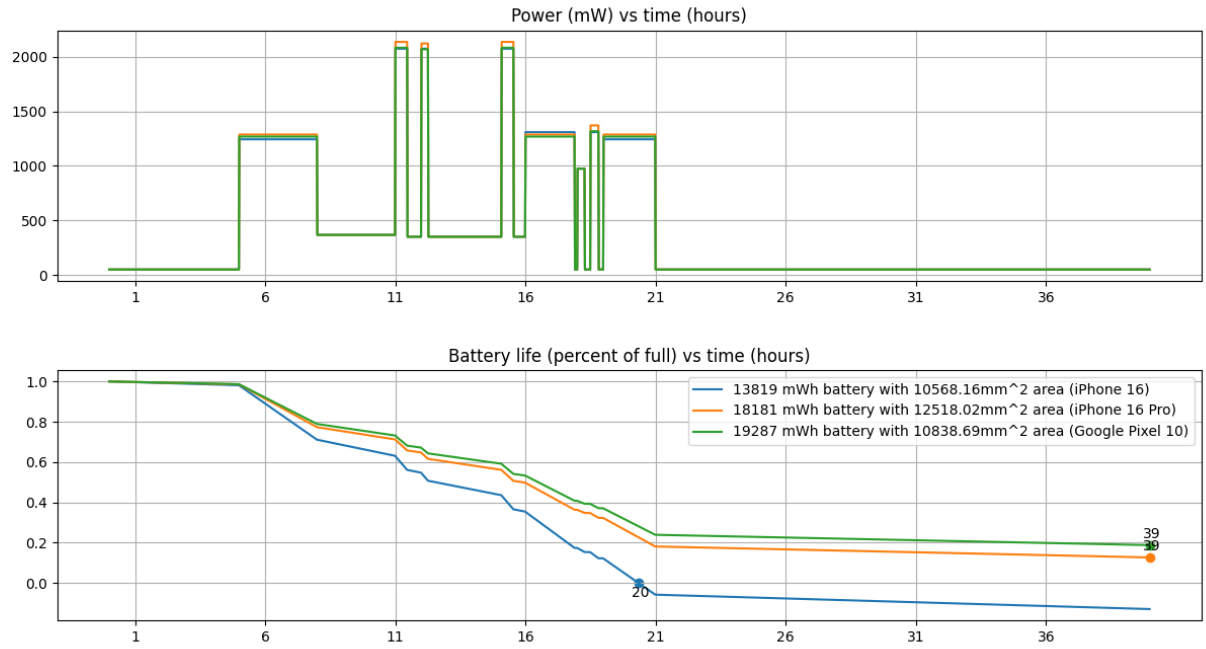


Figure 8: Screen Size analysis

The base high usage test case was with an iPhone 16 base model. Our analysis shows that while a bigger screen size does slightly increase power consumption, it is negligible compared to the benefits of having a bigger battery. In Figure 8 we compared the iPhone 16 Pro and the Google Pixel 10 specs to our iPhone 16 base test. Despite their bigger screen sizes, the added charge capacity of both phones caused the bigger models to have 19 more hours of battery life compared to the iPhone 16. This supports the market trend towards manufacturing bigger phones to extend battery life.

5.4.3 Network

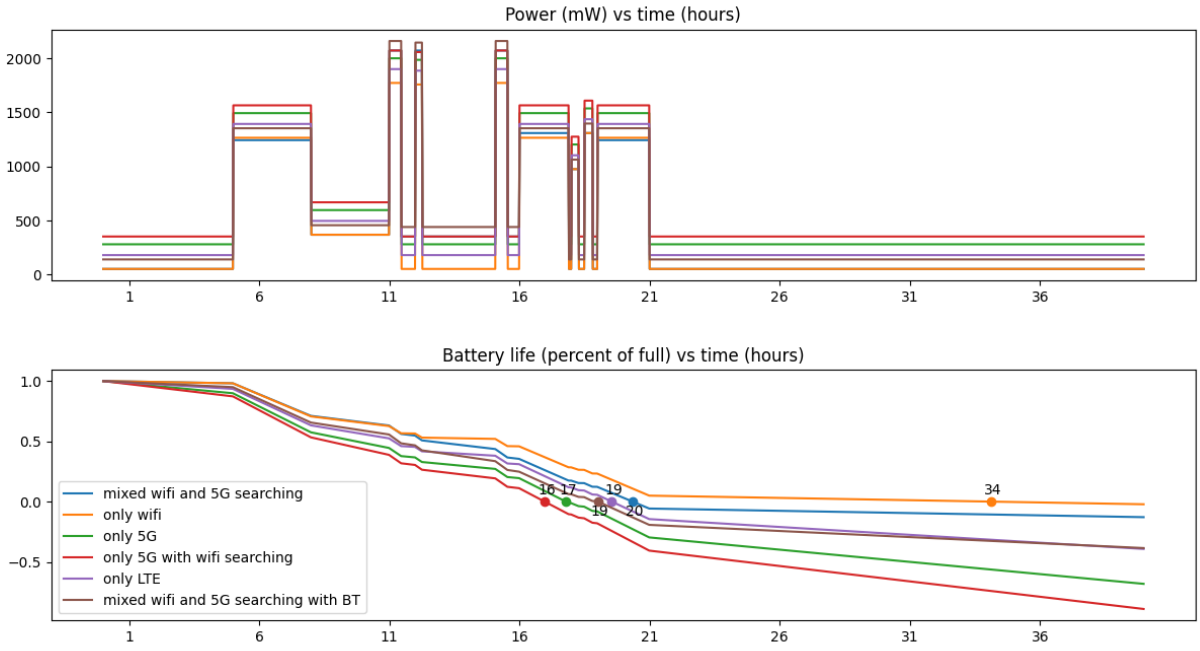


Figure 9: Network analysis

We observe that WiFi is the most important factor when it comes to battery life, demonstrated by Figure 9. The best network connection is a constant WiFi connection with a battery life of 34 hours, and the worst connection is a constant 5G connection while WiFi is on and searching with a battery life of 16 hours for the high usage behavior. Turning off your WiFi has a best case battery life savings of 1 hour, which is not very beneficial. LTE and Bluetooth are also low impact choices, only affecting battery life by an hour at most in practical applications. Thus the best way to save battery life from network connection preferences is to connect to WiFi as often as possible.

5.5 Model Reflection

5.5.1 Strengths

Our model is able to predict the approximate **time-to-empty** under different conditions, e.g. network connectivity and app usage. Our ***continuous-time model*** takes many aspects of modern smartphones into account, e.g. network connectivity and different displays.

5.5.2 Weaknesses

Due to a lack of data and time, not every aspect of smartphone power consumption is included in the model and we could only test our model on our phones, which are all iPhones. Some mathematical concepts in our model had to be simplified as well and thus do not present the full picture of a smartphones state of charge.

5.6 Future Work

More aspects of network connectivity effects on smartphone power usage need to be studied and given mathematical form. Idle power consumption is difficult to put numbers to and the last wide-scale data survey is now outdated because of how fast smartphone technology progresses. The model also does not account for loss of battery capacity over the life cycle and would need to implemented for accurate estimations of **SOC** and **time-to-empty** going forward. Overall, smartphone battery consumption is tedious to approximate and challenging to predict perfectly.

6 Recommendations

The most influential factor to battery life was WiFi connection. A constant WiFi connection yielded a 14-hour increase in battery life compared to normal usage. Users are thus recommended to use WiFi as much as possible to preserve battery life. This implementation is difficult for users who spend a lot of time outside or at locations without public WiFi, making it nonapplicable to a large group of individuals. The next most influential usage factor was brightness with a 5 hour increase in battery life for 10 percent brightness compared to 50 percent brightness. Users are thus recommended to reduce brightness as much as possible while sustaining phone usability. Finally, phone battery size plays a significant role in battery life for all usage behaviors, with bigger phones such as the iPhone 16 Pro and the Google Pixel 10 yielding almost 20 hours of extra battery life compared to the iPhone 16 base model, implying that investing in bigger phones has a strong impact on battery life.

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